Acta Montanistica Slovaca
ISSN 1335-1788
actamont.tuke.sk

A novel approach to commercial property valuation: Successive term indexing and its competitive implications

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Funding information:
Funding Agency: Slovak Research and Development Agency
Grant Number: APVV-22-0524, APVV-23-0562, APVV-23-0319

How to cite this article:
Tahotný, L., Suchý, V., Schönfeld, J. and Rózsa, Z. (2024), A novel approach to commercial property valuation: Successive term indexing and its competitive implications, *Acta Monstanistica Slovaca*, Volume 29 (2), 500-512

DOI:
https://doi.org/10.46544/AMS.v29i2.21

Abstract
The development of innovative valuation models in the commercial real estate sector is crucial for enhancing competitiveness, as they provide stakeholders with the accuracy and adaptability needed to navigate and capitalize in an increasingly complex market landscape. This paper aims to improve initial valuations provided by real estate agents by updating their timeliness while also enhancing their accuracy. Leveraging statistical techniques based on hedonic regression, it introduces a novel mechanism, successive term indexing, enabling the reassessment of widely varying commercial properties with initial assessments that are at least one term old, where a term typically encompasses one year. The model's novelty lies in its approach to indexing individual property characteristics across two successive terms, using a k-means algorithm to categorize all numerical variables and stepwise selection. The former enables differing index values for varying sizes, while the latter allows dynamic evaluation of the significance of regressors in time. Applied to data from a banking institution, the model showcases strong predictive accuracy with unique reassessment ratios ranging from -3.8% to 5.2% for 2022. With its nuanced analysis of market dynamics and indexing capabilities, the mechanism intersects the elements of PPIs and AVMs, presenting a significant methodological advancement and a practical, simple-to-use tool for valuation.

Keywords
Commercial property, Hedonic regression, Risk analysis, Property price indices

Introduction

In a dynamic real estate market, accurately valuing commercial real estate is a competitive advantage (Deppner & Cajias, 2024; Florêncio & de Alencar, 2020; Stasiak, 2023). An accurate valuation provides a solid basis for making informed decisions for investors. Moreover, it allows for identifying potentially profitable investments and accurately assessing risk, which is crucial in a market prone to rapid changes due to economic trends or regulatory changes (Jung et al., 2022). Lenders use real estate appraisals to determine safe loan amounts, using the property's value as collateral against the value of the loan. This risk management tool is vital to maintaining a competitive edge in the financial sector and ensures that it can operate safely without exceeding the limits of prudential lending (Griffin & Priest, 2023). Insurers also use these valuations to competitively price their premiums and set appropriate coverage limits, ensuring optimal profitability while avoiding the pitfalls of under- or over-insurance (Bogin & Shui, 2020). Likewise, accurate assessments ensure municipalities can collect fair property taxes, which is essential to maintaining budget balance and effectively funding public services (Fisch, 2022; Zhang et al., 2024). Overall, it can be said that in the competitive field of commercial real estate, accurate real estate valuation is more than just a financial tool – it is a strategic tool that improves decision-making, mitigates risks, and supports a stronger competitive position of stakeholders (Doumpos et al., 2021; Reck et al., 2023).

The literature on commercial real estate valuation underscores its complexity, which stems from the heterogeneity of commercial real estate, including a wide range of types, from office buildings to industrial sites (Gabrielli & French, 2020). Each category is affected by different factors, significantly different from those that affect the value of residential real estate (Feng & Iii, 2023; Sing et al., 2022; Stasiak, 2023). In addition, commercial real estate focuses mainly on income generation potential, which brings additional layers of complexity to their valuation. Key financial metrics, such as operating costs or occupancy rates, are crucial to evaluating a property's profitability but are often not readily available or consistently reported (Metelski & Sobieraj, 2022). This lack of transparency and uniform data further complicates accurately assessing commercial real estate value and potential return on investment. The challenge is heightened by the need to understand and incorporate these variables into statistical models that must be sophisticated enough to account for commercial real estate markets' diverse and dynamic nature (Bin et al., 2017; Boshoff & de Kock, 2013; Hill & Steurer, 2020; Oust et al., 2023).

Despite the increasing complexity of valuation processes and rapidly evolving market conditions, the primary methodologies used in the real estate valuation industry have remained remarkably stable over the past few decades (Krämer et al., 2023; Sivák et al., 2024; Vrbka et al., 2023). Even if they are reliable, they often struggle with timeliness and the integration of dynamic market data, especially when reassessments require significant market changes. This indicates a considerable research gap in the industry's adaptation to modern tools and techniques that could increase valuation accuracy and efficiency. Therefore, developing models that accurately measure commercial real estate prices is becoming increasingly important (Deppner et al., 2023; Feng & Iii, 2023; Jung et al., 2022; Wang et al., 2023).

Following the identified research gap, this paper aims to refine and improve upon initial valuations provided by real estate agents, leveraging statistical techniques to enhance the accuracy and efficiency of commercial property valuation and thus introducing a novel statistical model designed to address these challenges by enabling the reassessment of commercial properties with initial assessments that are at least one term old, where a term typically encompasses one year.

The proposed model stands at the intersection of technological innovation and practical application, offering significant benefits to various stakeholders in the real estate domain. Firstly, the study introduces a novel methodology at the confluence of Property Price Indices (PPIs) and Automated Valuation Models (AVMs), marking a unique contribution to the literature by indexing property features instead of forecasting prices. This approach, unseen in existing literature, opens a new research avenue, emphasizing the model's resilience against bias typical for linear methods, as noted by Doumpos et al. (2021) and Bin et al. (2017). Secondly, appraiser offices, which traditionally relied on manual reassessment processes limited by the scarcity of available information, stand to gain immensely from an approach that systematically incorporates broader data sets and analytical rigor. Similarly, investors and banking institutions will find the model invaluable for maintaining timely and precise control over their mortgage portfolios, thereby mitigating risk and optimizing asset management strategies.

The rest of the paper is organized as follows. The theoretical section underscores the critical role of accurate real estate valuation in the global economy, emphasizing its necessity for investment decisions, risk assessment, and financial stability. It highlights the unique challenges posed by the heterogeneous nature of commercial properties and the significant consequences of market inefficiencies, emphasizing the need for sophisticated valuation methods that consider physical, economic, and legal contexts to align with market expectations and adapt to technological advances. The methodology section outlines a process of data preparation, including information about cleaning and transforming data for regression analysis. In the results section, the paper presents the created model and discusses its significance for science and practice. In the conclusion, the paper also presents the limits of the chosen research approach and recommendations for further research.

Theoretical Background

Challenges and imperatives in commercial real estate valuation: insights from heterogeneity, market inefficiencies, and technological evolution

Commercial real estate remains one of the most valuable assets in the global economy, with accurate valuation playing a pivotal role in many investment decisions. They are characterized by infrequent trading and heterogeneity, and therefore, their valuation is quite a challenge in the context that their price fluctuations have profound consequences and significantly affect individual wealth and financial security, as highlighted by Bittencourt et al. (2022) and Jafary et al. (2022). However, understanding their value is essential not only for investors but also for the broader economic environment (Bittencourt et al., 2022; Jafary et al., 2022; Renigier-Biłozor et al., 2022).

According to Silver (2022), the diverse nature of these properties requires great effort in their valuation, supporting a multi-billion dollar industry. Deppner et al. (2023) further emphasize that the importance of valuation also justifies the considerable resources allocated to the valuation process.

Valuation is inherently individualized, considering not only the physical properties of real estate but also their economic and legal context. Accurate valuation depends on statistical methods that require comprehensive data on the transaction prices of comparable properties. This data should reflect the impact of various characteristics on property prices and meet market value conditions, including the timeliness of transactions, to ensure they align with current market expectations (Chegut et al., 2013; Jafary et al., 2024).

However, meeting these ideal conditions can be challenging. Real estate market inefficiencies mean that market prices may not fully reflect changes in the economic environment, making them an unreliable sole basis for valuation. Furthermore, as Stasiak (2023) points out, market participants generally lack awareness about how individual property characteristics—such as layout, age, and views—affect prices (Stasiak, 2023).

The importance of accurate real estate valuation goes beyond market efficiency. Oust et al. (2020) emphasize that reducing uncertainty in real estate transactions is crucial, especially in light of the global financial crisis (Oust et al., 2020). This period has highlighted the dangers of mis-valuation, with Europe witnessing significant real estate overvaluation that increased financial risks. The security provided during these inflated valuations often proved insufficient to cover losses, leading to increased scrutiny and criticism of real estate appraisers. According to de La Paz & Tárraga (2022) and Eriksen et al. (2020), this has pressured appraisers to align their valuations with accurate market values to mitigate financial instability (de La Paz & Tárraga, 2022; Eriksen et al., 2020).

Commercial real estate appraisers must navigate a multifaceted environment where technical skills, continuing education, and ethical integrity are paramount. The ability to effectively balance these demands is what defines their success and, thus, the trust placed in the valuation process by the wider market (Matysiak, 2023; Newell et al., 2010; van der Walt & Boshoff, 2017).

First, the complexity inherent in real estate valuation requires appraisers to apply a combination of standardized and innovative approaches. According to Bellman & Öhman (2016), appraisers often show a strong uniformity in their thinking when appraising commercial real estate, which can be both a strength and a limitation. While this homogeneity helps maintain consistency across valuations, it can also hinder flexibility and the ability to adapt to new market conditions (Bellman & Öhman, 2016; Gil & Pelon, 2023).

In addition, the valuation environment is heavily influenced by external economic factors such as inflation and growth, which directly affect the future income potential of real estate. Enever et al. (2014) highlight the specific challenges of real estate valuation under different economic and rental conditions that can drastically affect investment valuation. This complexity is compounded by regulatory requirements and environmental issues, where appraisers must navigate additional layers of compliance and dispute resolution related to property damage and creditor obligations (Borges et al., 2017; Vochozka et al., 2023).

Appraisal bias and the competitive nature of the industry further complicate the appraiser's role. Conklin et al. (2020) discuss how competition can lead to inflated valuations that not only affect individual transactions but can also have broader implications for the mortgage market and financial stability (Conklin et al., 2023).

Finally, the reliability of information sources and technological changes remains an ongoing challenge in commercial real estate valuation. Bellman (2018) emphasizes that accurate market valuations are highly dependent on reliable data on rental income and discount rates, which can vary widely across regions. Technological change and globalization also pose significant challenges. As markets become increasingly connected and technology-driven, appraisers must constantly update their methods and tools to remain relevant and effective. Źróbek et al. (2020) note the importance of integrating new technologies and adapting to changing consumer expectations that are reshaping the real estate landscape.

Delineating methodologies in real estate valuation: automated valuation models versus price performance indices

To establish a clear foundation for this review, it is appropriate first to delineate the scope between automated valuation models (AVMs) and property price indices (PPIs) in real estate valuation. AVMs apply mathematical modelling, typically including hedonic regression, to estimate the market value of individual properties by analyzing attributes such as location and property characteristics, offering specific property appraisals (Glumac & Des Rosiers, 2021; Jeon et al., 2023; Sing et al., 2022; Valier, 2020). While they offer significant advantages in speed and cost-effectiveness, their accuracy depends on a complex interplay of factors. Ensuring the reliability of AVM outputs requires careful attention to data quality, the appropriateness of the models used, and the continuous integration of new technologies and data types. As the field advances, so must the methodologies and technologies that underpin these valuable tools to ensure they remain effective in the ever-evolving real estate valuation environment (Bittencourt et al., 2022; Jafary et al., 2022, 2024; Krämer et al., 2023; Valier, 2020).

In contrast, PPIs measure the price changes of real estate markets over time, providing an aggregated perspective rather than valuations for individual properties (Hill & Steurer, 2020; Laopodis, 2022). In the complex field of real estate valuation, methods such as repeat sales and appraisal indices stand out as crucial tools for developing precise Property Price Indices (PPIs). These techniques are essential in capturing the nuanced effects of property-specific characteristics and local market dynamics on property prices. They represent crucial advancements in understanding and documenting property price dynamics. By addressing the multifaceted nature of real estate markets and accommodating regional disparities, these techniques offer more accurate and meaningful insights into property values, essential for buyers, sellers, investors, and policymakers alike. However, the ongoing challenge lies in refining these models to enhance their precision and applicability across diverse real estate landscapes (Agarwal et al., 2021; Gong & De Haan, 2018; Silver, 2022).

This distinction is crucial for understanding the varied applications of each method in the real estate sector (Bin et al., 2017). With their differing scope, applicable procedures also vary. To achieve precise property valuation, AVMs often utilize sophisticated algorithms, including machine learning models like recurrent neural networks and boosting trees (Bin et al., 2017). Conversely, PPIs typically use methods such as repeat sales and appraisal indices, which focus on capturing broad market trends rather than the values of individual properties. Although some statistical techniques like hedonic regression can be applied to both, their objectives dictate methodological preferences (Eurostat et al., 2017).

Numerous papers addressing commercial estate highlight its enhanced complexity, which makes statistical modelling more challenging. This complexity arises from the diverse nature of commercial properties - ranging from offices to industrial sites, each influenced by unique factors such as lease structures and economic dependencies. Unlike residential properties, commercial real estate places a significant emphasis on income generation capabilities, necessitating information on aspects like operating expenses or occupancy rates, which are often scarcely known (Bin et al., 2017; Boshoff & de Kock, 2013; Chaney et al., 2012; ECB, 2014; EUROSTAT, 2017).

Several methodological approaches exist, including previously mentioned appraisal-based methods, repeated sales methods, and hedonic regression methods (Hill & Steurer, 2020). This section primarily focuses on the latter, as they leverage the same statistical apparatus as this paper. Hedonic methods, while particularly effective in dissecting the overall price index into distinct property characteristics, are criticized for their heavy reliance on aggregate transaction data, requiring extensive information on property characteristics, which complicates their implementation (W. E. Diewert et al., 2015). Additionally, they face issues with multicollinearity and variability in results due to different model specifications. In a subsequent study exploring the prices of REITs in Tokyo, Japan, E. Diewert and Shimizu (2017) introduced the Builder's model, expanding the regression model by decomposing the property price into land and structure, also enabling the accounting for the property's depreciation.

Doumpos et al. (2021) and Bin et al. (2017) both evaluate linear regression in real estate valuation, acknowledging its utility while pointing out limitations. Doumpos et al. (2021) highlight its limitations in capturing spatial dynamics, suggesting an enhancement through spatial information integration and addressing oversimplification and bias (Doumpos et al., 2021). Bin et al. (2017) propose an ensemble learning model to overcome linear regression's limitations, notably its failure to capture complex market dynamics (Bin et al., 2017). Both studies underscore the need for advanced methodologies to improve predictive performance in real estate valuation.

Methodology

The section first describes the rigorous data cleaning and variable transformation process, followed by the application of linear regression, highlighting the steps taken to refine the analysis and ensure the highest data quality. The subjecting market, the commercial sector of the Czech property market reflects characteristics typical of a developing financial market. Although the Czech financial market has matured significantly since the early

1990s, it is widely believed that it still exhibits relatively lower liquidity compared to more established Western markets. This situation is particularly evident in the commercial property sector, where a limited number of large participants dominate the market, potentially highlighting the impact of factors such as prejudiced appraisers, undermining the overall quality of data (Deppner & Cajias, 2024; Stokes & Cox, 2023; Wan & Lindenthal, 2023).

Dataset preparation

Underpinning this research is a comprehensive dataset provided by a significant Czech banking institution, initially encompassing over 20,000 observations of commercial properties. These properties, which were subject to mortgages at the time of their initial assessment, span from 2009 to 2022 and originate solely from appraisal assessments. However, after controlling for quality and focusing on the years of interest for this paper, namely 2021 and 2022, only 1,949 observations remain for use in the analysis. It is also important to note that the sample is non-probabilistic, as it exclusively includes properties mortgaged through this single banking institution, which may limit the diversity and generalizability of the findings. This issue is further explained when discussing the limitations of the model. However, concerning time features, the dataset exhibits characteristics of a pooled cross-sectional design, wherein new observations are generated through the sampling process each period. This structure inherently supports the division of the dataset into distinct cross-sections for each period, providing an optimal format for the methodology employed.

Modifying the dataset involved the removal of duplicate, incomplete, or highly improbable values and variables from the dataset. Therefore, the data quality was evaluated in terms of accuracy and completeness. Although interventions in the data, particularly in individual observations, are generally undesirable (as they may lead to the systematic exclusion of data, which would violate the data-generating process), it was necessary to ensure the highest quality of data with the utmost caution, as the quality of the model subsequently depends on it. Initial adjustments to the dataset were conducted in MS Excel, with the later involvement of R for replicability and reversibility of some modifications.

The initial step in data processing was the definition of the types of properties and the relevant years included in the model. This was done because the analyzed data originated only from commercial subjects' mortgages, which include highly varying types of real estate, many of which either did not meet the nature of commercial property (single-family houses and apartments) or were objects with insufficient information regarding their type (for example restaurant facilities, hotels, or educational facilities). The types of properties left for analysis can be generalized as displayed below:

- Administrative facilities (non-residential unit - administrative)
- Multipurpose facilities (service and public amenities object - multipurpose, polyfunctional object without apartments, complex - multipurpose, hall - multipurpose)
- Agricultural facilities (complex - agricultural, hall - agricultural)
- Manufacturing and storage facilities (complex - storage, complex - manufacturing, hall - storage, hall - manufacturing)
- Retail, supermarkets, hypermarkets (non-residential unit - commercial, service and public amenities object - store, service and public amenities object - supermarket, service and public amenities object - hypermarket)

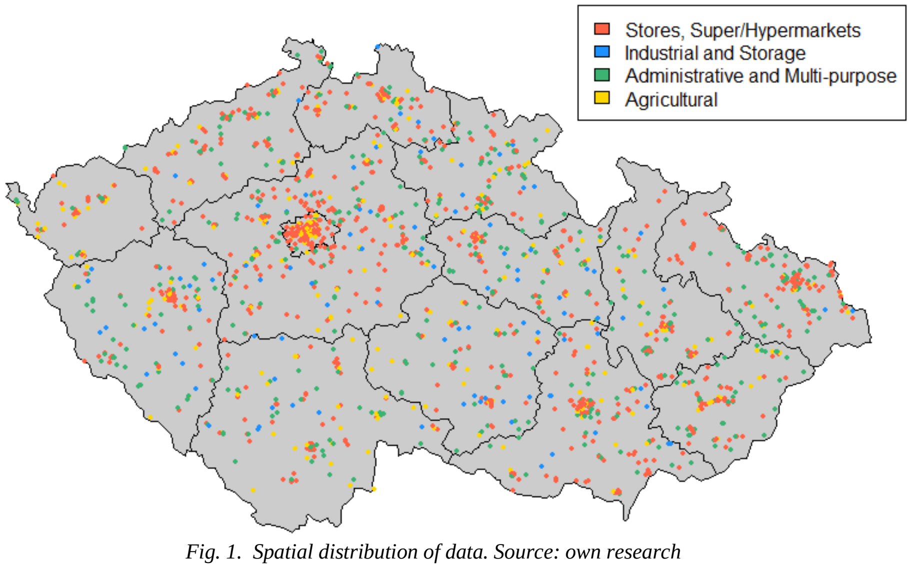

Fig. 1. Spatial distribution of data. Source: own research

Next, missing and incorrect values were addressed. These likely originate from the fact that real estate agents collect and write the data by hand. Caution was put on removing only incorrect values (such as facilities with an area of 1 m^2) and not extreme values, i.e. outliers. A substantial part of missing values that were deemed significant for the model were approximated using other attributes (e.g., m^2, for which a separate prioritization algorithm was developed due to the information being split among several other columns, each missing different values).

In the following step, the dataset underwent augmentation with externally acquired economic variables, which included information on population size, unemployment rate, and crimes per capita. All these data were freely exported from the public database of the Czech Statistical Office. The goal was to obtain the data at the most granular administrative level (municipalities), which was only achieved for the population size variable. The remaining two variables were obtained for districts.

The final intervention in the dataset was transforming numerical variables into categorical ones. The reason for this is straightforward - as the goal of the succeeding regression analysis is to compare the sum of coefficients of characteristics that each specific property has, it is desirable that we can observe changes with varying sizes of features such as m^2, for which we need several estimates for the different sizes of the feature. For this purpose, the k-means clustering algorithm was utilized, resulting in splitting each numerical variable into three clusters according to their sizes - small, medium, and large.

Though not completely necessary, given the nature of the model, the dataset for regression t - 1 was further refined by splitting it into a 90/10 train/test partition. The reason the test set was only created for regression t - 1 is that those are the data we endeavour to reassess on prices of term t. Finally, the dataset was left with 1949 observations subject to the following analysis (i.e., fit the defined time window). The time window is defined as 365 days from the date of the newest observation for regression t (1006 observations) and 365 to 720 days for regression t - 1 (943 observations), which in this case roughly equals years 2022 and 2021. In this manner, the time window can shift with almost no effort, making it possible to reevaluate properties dating as far as the underlying dataset goes.

Model creation

One potential issue stems from the model selection - of the existing 17 variables (see table below), both regression t and t - 1 have to be fitted with exactly the same combination of features in order to be directly comparable to each other. However, the statistical significances of regressors in these two models usually differ. For this matter, linear model selection methods were employed for each of the two equations, specifically forward stepwise selection. In this algorithm, features are added one by one to the equation, prioritizing those improving the pre-selected goodness-of-fit measures the most, which, in our case, was the Akaike information criterion. Therefore, the features selected for inclusion in the model were those that 1) yielded significant enhancement to both regression equations and 2) met the 5% significance level criterion. Joint F-tests were utilized to assess the significance of predictors having more than two levels.

Tab. 1. Description of the variables. Source: own research

Variable name	**Description**
Type	Type of the property based on purpose of use, see Chapter 3.1
Category	Classification based on the type of property (store, industry hall, polyfunctional object, …)
Location	Property location (centre, residential area, etc.)
Heating	Type of heating of the property
Construction	Type of property construction
Condition	Technical condition of the property
m2	Categorized area of the property in square meters
Inhabitants	Categorized population in the municipality
Age	Categorized age of the property in years
Electricity	Connection to the electrical grid
Water	Connection to the water supply network

Railway	Nearby railway station or stop
Waste	Connection to the sewage system
Public transport	Nearby public transport stop (tram, metro, inter-city bus)
Bus	Nearby inter-city bus stop
Road	Property connected to at least a secondary class road
Highway	Nearby highway access

Breusch-Pagan test and White's test were then used to recognize the presence of heteroskedasticity for all estimated equations. With most of the stepwise selection estimated equations, we were not able to reject the null hypothesis about homoskedasticity, meaning no evidence of heteroskedasticity was found. Nevertheless, due to the few heteroskedastic models, as well as both the economic and statistical logic, it was decided to transform the dependent variable (the nominal price of the property) using natural logarithm to both mitigate the variances and make better sense of the data.

Finally, what we call the reassessing ratios is created by deploying a custom function developed in R. This function is meticulously designed to match the characteristics of each property with corresponding regressors. For instance, if a property is identified as being constructed from concrete, out of all levels under the construction variable, only the coefficient pertaining to concrete is selected. It is important to note that the sum of coefficients also includes the intercept. This inclusion is crucial because each feature has one level omitted to prevent the so-called dummy trap, where some levels are not explicitly displayed but are inherently part of the intercept (e.g., the coefficient for m^2 - large is not displayed, for it is already part of the intercept). In this fashion, the function then aggregates all characteristics that align with the property's profile for both periods, t and t - 1.

$$reassesing\ ratios = \frac{intercept_t + \sum relevant\ coefficients_t}{intercept_{t-1} + \sum relevant\ coefficients_{t-1}} \tag{1}$$

By calculating the sum of relevant coefficients for t and dividing them by the same sum for t - 1, the function effectively yields the ratios used for reassessment. Moreover, the computation of these ratios thoughtfully considers the magnitudes of the coefficients, ensuring that those with a higher impact on price also play a more significant part in the sum of coefficients. This nuanced approach not only enhances the precision of our analysis but also facilitates a deeper understanding of temporal dynamics in property characteristics, as reflected through these ratios, ensuring a comprehensive assessment that accounts for both the presence and the significance of various property features.

Results and Discussion

The regression equation yielded by the procedure described contained 9 variables, all of which are, in a simplified manner, shown below. Recall that all the numerical variables had been converted to categorical.

$$\begin{aligned}\log(price) \sim & m2 + Category + Inhabitants + Age + Construction + Public\ transport \\ & + Type + Condition + Heating\end{aligned} \tag{2}$$

The distinction between' Category' and' Type' might pose a challenge; to clarify,' Category' refers to the classification of properties (e.g., Administrative and multipurpose facilities, etc.), whereas' Type' denotes the actual construction type of the property, such as commercial units, industrial halls or complexes (not to be confused with 'Construction' which carries information about the construction material). Comprehensive summaries of both regressions included in the model are available in the appendix.

Upon applying the gained reassessing ratios to the test dataset derived from term t - 1, it came out that among 105 properties in the test set, 89 exhibited an increase in value over the specified period, with the most significant appreciation of 5.2%. Conversely, the property that saw the largest decrease in value underwent a 3.8% depreciation. On average, the properties in the test dataset realized a 1.33% gain, underscoring a general trend of value appreciation among the assessed properties.

Comparison with other studies, however, is not straightforward, mainly due to the distinct methodology employed by this paper, aiming to reassess previously existing appraisals to remain timely rather than predicting the price of unseen property. Its basing apparatus, the hedonic model, is often measured by MSE, which, due to the nature of reassessing appraisals, we are not able to compute here. We therefore compare the findings of papers that concern PPI on commercial property. For instance, using Lowe PPI with similar data sources (a combination of appraisal and transactional data), Knetsch (2021) gained an average growth rate of 2.4% over the years 1995 – 2019 in Germany. These results are not far from those of this paper, while both the market and the data sources are comparable. Similarly, in an ECB (2014) release, experimental indicators of commercial property prices showed similar growth rates for 2004 - 2013. However, it is noted that due to the short time window and the impact of the 2008 crisis, the yearly means are skewed. Gatzlaff and Holmes (2013) based their index on property tax records in Florida using an augmented method of repeated sales, concluding an average quarterly growth of 1.74% for properties valued over $2.5 million and 1.17% otherwise. However, comparing results from such distinct environments does not yield highly significant insights.

For a true validation of the results, a set of panel data where each property has at least two appraisals is needed. Provided these data are of sufficient quality, the "true" growth rate can be calculated and compared to the rate stated by the model. At the time of writing, such data are not yet available. However, their collection is ongoing, as financial institutions are obligated to re-appraise each property in their lending portfolio after a specified period.

It is crucial to remember that implementing hedonic (or hedonic-based) models has considerable shortcomings, as bias will always arise from the inability to include all characteristics impacting a property's price. Diewert and Shimizu (2017) specifically mention the inability to account for differing factors influencing the prices of land and structures, as well as the failure of most such models to accurately account for structure depreciation. Another issue stems from the data collection process: only mortgages from one banking institution were emphasized, meaning the results likely won't generalize well to the broader population. However, efforts to integrate datasets from multiple institutions exist, potentially mitigating this issue in the future. Additionally, the logarithmic transformation imposed on the dependent variable is known to mitigate the effect of regressors on that variable, which is also a concern.

Science Implications

A novel methodology merging elements of Property Price Indices (PPIs) and Automated Valuation Models (AVMs) was introduced, offering a significant contribution to the literature. The innovation lies in maintaining the currency of existing property valuations—originally derived from appraisals but potentially also from AVMs or other sources—by updating them periodically using principles of hedonic regression. These adjustments allow for the properties' features to be indexed over time, facilitating the creation of nuanced, time-sensitive indices that reflect changes in property values more accurately and dynamically. Additionally, the method is not only capable of updating appraisals but also has the potential to mitigate some of the biases and errors commonly introduced by appraisers, thereby increasing the accuracy of the valuations. This corrective capacity stems from the regression's ability to systematically adjust valuations based on a wide array of quantifiable property characteristics.

Moreover, the efficiency of commercial property valuation is enhanced, as the method introduced can reevaluate any property, provided one can withstand biases stemming from either a lack of information about certain types of properties or from not having sufficiently high-quality observations. This flexibility and efficiency make the model a robust tool in the real estate valuation field, optimizing both the reliability and utility of property appraisals over time.

Practical Implications

Firstly, the availability of a highly detailed and timely valuation dataset enables financial institutions to make better-informed decisions during the mortgage underwriting and refinancing processes. This enhanced decision-making capability not only influences the determination of loan amounts, loan-to-value ratios, and interest rates offered to borrowers but also provides these institutions with a significant competitive advantage. Specifically, it allows them to manage their loan portfolios more precisely, with a particular emphasis on risk analysis (Jafary et al., 2024).

Secondly, the timely availability of commercial property market data carries substantial practical implications for regulatory bodies. Such data facilitates a more informed decision-making process, allowing regulators to respond proactively to economic signals. For instance, as Chaney et al. (2012) highlighted, shifts in commercial property markets often precede broader economic changes due to their sensitivity to business dynamics, such as employment rates and retail sales. Accurate and current property indices enable regulators to monitor these market shifts closely, which is crucial for anticipating and mitigating potential economic downturns, as evidenced during the 2008 financial crisis.

Finally, the advancements provided by this research benefit appraisal offices, small and medium enterprises (SMEs), and small investors by laying the groundwork for robust PPIs. For appraisal offices, access to updated and detailed valuation datasets ensures that appraisals accurately reflect current market conditions, thereby enhancing the credibility and reliability of their assessments. SMEs and small investors, who often face challenges due to limited access to market data, stand to benefit from these indices. The creation of tailored PPIs serves as a critical tool for these groups, enabling them to make informed strategic decisions and investment analyses. This could mean securing better financing terms for SMEs by accurately demonstrating property values to lenders. For small investors, it provides a means to assess potential investments more accurately, helping to identify undervalued properties or markets with growth potential. This approach democratizes access to crucial market information, leveling the playing field and fostering more competitive and resilient commercial property markets.

Conclusion

The role of property valuation is integral to maintaining financial stability and transparency in the real estate market. Ensuring that these valuations accurately reflect true market values is not just a technical necessity but a fundamental requirement to safeguard economic security and trust in financial systems worldwide.

This paper embarked on enhancing the re-evaluation process for commercial properties, utilizing a dataset from a major Czech banking subject. It culminated in a robust statistical model, distinguished by its implementation ease and accessibility for users without specialized expertise. Unlike complex contemporary models, our approach uses a straightforward statistical apparatus. The model's introduction of *reassessing ratios*, based on two linear regressions with adjusted R^2 values greater than 0.6, offers a nuanced analysis, capturing market dynamics effectively. These ratios varied from -3.8% to 5.2% for 2022, indicating the model's practical utility in real-world settings.

In the context of the methodology used, it is important to recall some research limitations of the presented approach, including the need for broader economic validation, despite field specialist support. The model currently covers common commercial property types, with a scope for expanding property type inclusivity. The study also underscores the importance of data quality, laying the groundwork for future exploration to enhance validation techniques and broaden the model's applicability.

Future research should explore advanced statistical methods, such as non-parametric regression, and enhance the incorporation of various other property types. This work ultimately aims to establish a first-in-the-country, industry-wide index for commercial and residential properties, setting a new benchmark in property valuation and encouraging further innovation in the field. Acknowledging the model's current limitations, this foundation advances the accuracy and applicability of property valuations, emphasizing the importance of diverse data and innovative techniques in real estate market analysis.

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Appendix

Tab. 2. Regression summaries. Source: own research

	log (Price)	
	Model t	**Model t-1**
Intercept	19.922*** (0.359)	20.910*** (0.397)
m2 – Medium	-1.364*** (0.261)	-1.783*** (0.288)
m2 – Small	-2.805*** (0.253)	-3.319*** (0.280)
category – Industry hall	-0.559*** (0.077)	-0.534*** (0.080)
category – Hypermarket	1.320*** (0.389)	1.302*** (0.250)
category – Commercial unit	-0.852*** (0.160)	-1.394*** (0.179)
category – Polyfunctional object	0.823*** (0.243)	0.198 (0.246)
category – Store/multipurpose	-0.289*** (0.083)	-0.346*** (0.086)
category – Supermarket	0.298* (0.153)	0.932*** (0.219)
inhabitants – Medium	-0.911*** (0.107)	-1.096*** (0.108)
inhabitants – Small	-0.456*** (0.129)	-0.688*** (0.134)
age – Medium	0.296*** (0.065)	0.310*** (0.067)
age – Small	-0.053 (0.068)	0.188** (0.076)
construction – Wooden	-0.416* (0.236)	-0.523* (0.309)
construction – Other	-0.171 (0.432)	-0.823*** (0.303)
construction – Metallie	-0.268***	-0.315***

	(0.103)	(0.111)
construction – Prefabricated	0.100 (0.103)	-0.142 (0.111)
construction – Brick	-0.376*** (0.083)	-0.681*** (0.099)
Public transport stop nearby	0.312*** (0.054)	0.219*** (0.058)
type – Retail, supermarkets, hypermarkets	0.087 (0.195)	0.064 (0.187)
type – Multipurpose facilities	0.716*** (0.221)	0.512** (0.222)
type – Manufacturing and storage facilities	0.675*** (0.232)	0.493** (0.233)
type – Agricultural facilities	0.684*** (0.252)	0.176 (0.255)
condition – For reconstruction	-0.175 (0.111)	-0.203** (0.095)
condition – New-build	0.490*** (0.110)	0.482*** (0.124)
condition – Well-kept	0.125* (0.065)	0.366*** (0.067)
heating – Local electricity	-0.358*** (0.111)	-0.385*** (0.113)
heating – Gas	-0.101 (0.076)	-0.167** (0.075)
heating – Solid fuels	-0.390*** (0.108)	-0.568*** (0.115)
heating – Heat pump	-0.130 (0.135)	-0.197 (0.150)
Observations R^2 Adjusted R^2	1,006 0.628 0.617	943 0.665 0.655
Note:	*p<0.1; ** p<0.05; *** p<0.01	